DSM_Machine_Learning_Project3_Satish_Doiphode

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DSM_Machine_Learning_Prc

Code Python 3

```
[3]: """Problem -1
We can predict whether a person makes over 50K a year with the accuracy approx 98%.

Problem -2
By feature selection we have performed above we know that some important factors are 'age', 'fnlwgt', 'education_num', 'capital_gain', 'hours_per_week'

Problem -3
by accuracy comparision performed above we can see that Random forest gives better result than other algorithm."""
```

```
[3]: "Problem -1\nWe can predict whether a person makes over 50K a year with the accuracy approx 98%.\n\nProblem -2\nBy feature selection we have performed above we know that some important factors are 'age', 'fnlwgt', 'education_num', 'capital_gain', 'hours_per_week'\n\nProblem -3\nby accuracy comparision performed above we can see that Random forest gives better result than other algorithm."
```

```
[4]: # import various libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

```
[5]: # Read the data from given website
train_set = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.data', header = None)
test_set = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.test',
                      skiprows = 1, header = None) # skip a row for the test set
```

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Code

```
[6]: # Column labels taken from the file
col_labels = ['age', 'workclass', 'fnlwgt', 'education', 'education_num', 'marital_status', 'occupation',
              'relationship', 'race', 'sex', 'capital_gain', 'capital_loss', 'hours_per_week', 'native_country',
             'wage_class']
```

```
[7]: # column labels assigned to train and test dataset
train_set.columns = col_labels
test_set.columns = col_labels
```

```
[8]: train_set.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
age               32561 non-null int64
workclass         32561 non-null object
fnlwgt            32561 non-null int64
education         32561 non-null object
education_num     32561 non-null int64
marital_status    32561 non-null object
occupation        32561 non-null object
relationship      32561 non-null object
race              32561 non-null object
sex               32561 non-null object
capital_gain      32561 non-null int64
capital_loss      32561 non-null int64
hours_per_week    32561 non-null int64
native_country    32561 non-null object
wage_class        32561 non-null object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

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Code

```
[9]: test_set.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16281 entries, 0 to 16280
Data columns (total 15 columns):
age               16281 non-null int64
workclass         16281 non-null object
fnlwgt            16281 non-null int64
education         16281 non-null object
education_num     16281 non-null int64
marital_status    16281 non-null object
occupation        16281 non-null object
relationship      16281 non-null object
race              16281 non-null object
sex               16281 non-null object
capital_gain      16281 non-null int64
capital_loss      16281 non-null int64
hours_per_week    16281 non-null int64
native_country    16281 non-null object
wage_class        16281 non-null object
dtypes: int64(6), object(9)
memory usage: 1.9+ MB
```

```
[10]: # Replacing the ? in train set with nan and later droping those rows
train_set.replace(' ?', np.nan).dropna().shape

[10]: (30162, 15)
```

```
[11]: # Replacing the ? in test set with nan and later droping those rows
test_set.replace(' ?', np.nan).dropna().shape

[11]: (15060, 15)
```

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Code

[12]:
```
train_nomissing = train_set.replace(' ?', np.nan).dropna()
test_nomissing = test_set.replace(' ?', np.nan).dropna()
```

[13]:
```
#replacing the irregularities in the wage columns
test_nomissing['wage_class'] = test_nomissing.wage_class.replace({' <=50K.': ' <=50K', ' >50K.':' >50K'})
```

[14]:
```
train_nomissing['wage_class'].unique()
```

[14]:
```
array([' <=50K', ' >50K'], dtype=object)
```

[15]:
```
test_nomissing['wage_class'].unique()
```

[15]:
```
array([' <=50K', ' >50K'], dtype=object)
```

[16]:
```
# combining the datasets
df = pd.concat([train_nomissing, test_nomissing], axis = 0) # Stacks them vertically
```

[17]:
```
# Check the combined dataframe header
df.head()
```

[17]:

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native_country	wage_class
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K

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Code

[18]:
```
#Check the shape of the combined dataframe
df.shape
```

[18]:
```
(45222, 15)
```

[19]:
```
# view summary of combined dataframe - statistical information only about numerical columns will be shown
df.describe()
```

[19]:

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week
count	45222.000000	4.522200e+04	45222.000000	45222.000000	45222.000000	45222.000000
mean	38.547941	1.897347e+05	10.118460	1101.430344	88.595418	40.938017
std	13.217870	1.056392e+05	2.552881	7506.430084	404.956092	12.007508
min	17.000000	1.349200e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.173882e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783160e+05	10.000000	0.000000	0.000000	40.000000
75%	47.000000	2.379260e+05	13.000000	0.000000	0.000000	45.000000
max	90.000000	1.490400e+06	16.000000	99999.000000	4356.000000	99.000000

[20]:
```
#Calculate percentage of different-2 classes in the combined dataframe
from collections import Counter

dict = Counter(df['wage_class'])
print(f"dictionary with all classes : {dict}")
print(f"Keys for the different-2 classes : {dict.keys()}")
print(f"dict[' >50K'] : {dict[' >50K']} , dict[' <=50K'] : {dict[' <=50K']}")
print(f"Class 1 percentage : {dict[' >50K']/len(df)*100} , Class 2 percentage : {dict[' <=50K']/len(df)*100}")
```

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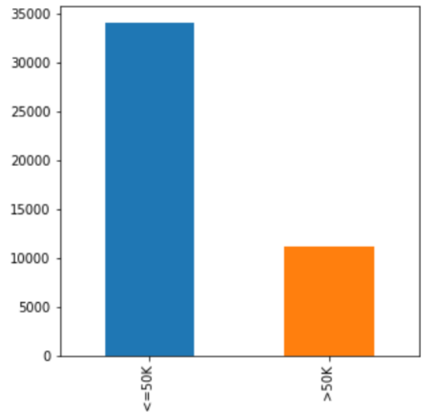
Code

```
dictionary with all classes : Counter({' <=50K': 34014, ' >50K': 11208})
Keys for the different-2 classes : dict_keys([' <=50K', ' >50K'])
dict[' >50K'] : 11208 , dict[' <=50K'] : 34014
Class 1 percentage : 24.78439697492371 , Class 2 percentage : 75.21560302507629
```

[21]:
```
#Visualize column salary of the dataframe
df['wage_class'].value_counts()

df['wage_class'].value_counts().plot(kind='bar',figsize=(5,5))
```

[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x146e14715f8>
```



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Code

[22]:
```
df['wage_class'] = df['wage_class'].map({' >50K': 1, ' <=50K': 0})
```

[23]:
```
"""Preprocessing (Handling Missing/Duplicate/Categorical data)"""
```

[23]:
```
'Preprocessing (Handling Missing/Duplicate/Categorical data)'
```

[24]:
```
#print information about missing data
print(f"Check count of the missing data in dataframe : {df.isna().any().count()}")

#handle missing data in the newly created dataframe if there is any
if df.isna().any().count() :
    df.fillna(value=-99999,axis=1,inplace=True)
    #print(f"\nheader of the new dataframe after handling of the missing data : \n{df1.head}")
    print("Info : Missing entries are updated in the dataframe")


#handle categorical data
df1 = pd.get_dummies(df)

#print information such as shape, duplicate entries in newly created dataframe
print(f"\nshape of the new dataframe before preprocessing : {df1.shape}")
print(f"Check count of the duplicated data in newly create dataframe : {df1.duplicated().sum()}")

#remove duplicates if there is any
if df1.duplicated().any().sum() :
    df1.drop_duplicates(inplace=True)
    print(f"\nshape of the new dataframe after removal of duplicate entries : {df1.shape}")
```

```
Check count of the missing data in dataframe : 15
Info : Missing entries are updated in the dataframe
```

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Code

```
shape of the new dataframe before preprocessing : (45222, 105)
Check count of the duplicated data in newly create dataframe : 47

shape of the new dataframe after removal of duplicate entries : (45175, 105)
```

[25]:
```python
#Split dataframe into df_x and df_y#Split da
df_x = df1.drop(['wage_class'], 1)
df_y = df1['wage_class']
```

[26]:
```python
from sklearn.ensemble import RandomForestClassifier

#Use RandomForestRegressor to check feature_importances
rfc = RandomForestClassifier(random_state=10)
rfc.fit(df_x, df_y)

feature_importances = pd.DataFrame({'feature':df_x.columns,'importance':np.round(rfc.feature_importances_,4)})
feature_importances = feature_importances.sort_values('importance',ascending=False).set_index('feature')
```

[27]:
```python
#Visualize top 20 features of the dataframe
feature_importances[:20].plot(kind='barh',figsize=(10,10))
```

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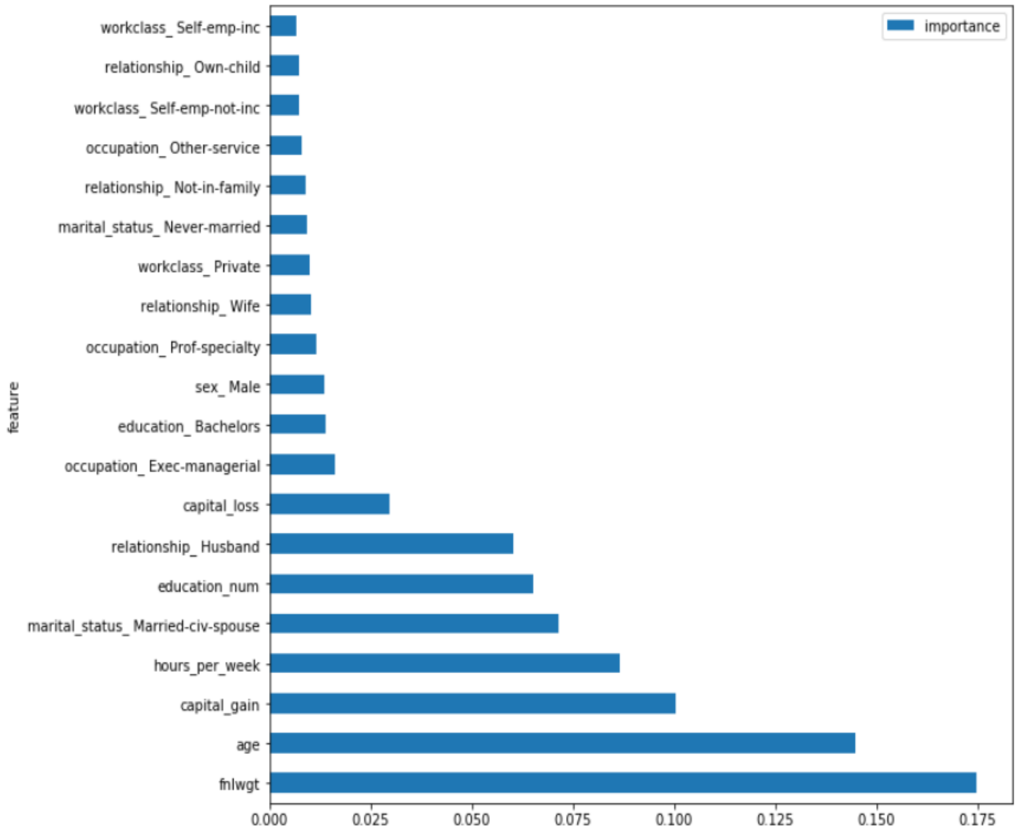
Code

[27]: <matplotlib.axes._subplots.AxesSubplot at 0x146e37f7400>



[28]:
```python
#Apply model on training and test dataset
from sklearn.model_selection import train_test_split
```

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DSM_Machine_Learning_Prc

Code

[28]:
```
#Apply model on training and test dataset
from sklearn.model_selection import train_test_split

# split dataset into train(75%),test(10%),cross-validation(15%)
x, x_test, y, y_test = train_test_split(df_x,df_y,test_size=1/3,train_size=2/3, random_state = 0)
x_train, x_cv, y_train, y_cv = train_test_split(x,y,test_size = 0.40,train_size =0.60, random_state = 0)
```

[29]:
```
#Apply logistic regression model on the dataset
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE

lr1 = LogisticRegression()
lr = RFE(lr1, 50)
lr.fit(x_train,y_train)
```

[29]:
```
RFE(estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False),
  n_features_to_select=50, step=1, verbose=0)
```

[30]:
```
#Apply decision tree classifier model on the dataset
from sklearn.tree import DecisionTreeClassifier

d_tree = DecisionTreeClassifier(min_samples_split=10, random_state=55, max_features=50)
d_tree.fit(x_train, y_train)
```

[30]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
            max_features=50, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=10,
            min_weight_fraction_leaf=0.0, presort=False, random_state=55,
            splitter='best')
```

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DSM_Machine_Learning_Prc

Code

[31]:
```
# Apply Bagging classifier on the dataset
from sklearn.ensemble import BaggingClassifier

Boosting = BaggingClassifier(n_estimators=200)
Boosting.fit(x_train,y_train)
```

[31]:
```
BaggingClassifier(base_estimator=None, bootstrap=True,
         bootstrap_features=False, max_features=1.0, max_samples=1.0,
         n_estimators=200, n_jobs=1, oob_score=False, random_state=None,
         verbose=0, warm_start=False)
```

[32]:
```
#Apply Random forest classifier on the dataset
rfc = RandomForestClassifier(random_state=55,max_features=50)
rfc.fit(df_x,df_y)
```

[32]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features=50, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
            oob_score=False, random_state=55, verbose=0, warm_start=False)
```

[33]:
```
#Analyse model performances using roc_auc_score and accuracy score
```

[34]:
```
from sklearn.metrics import r2_score, roc_auc_score, accuracy_score, confusion_matrix, roc_curve, auc
```

[35]:
```
models = pd.DataFrame(index=['train_ras','cv_ras','test_ras','accuracy_score'],
                      columns=['logistic_regression','decision_tree','random_forest','xgboost'])
```

[36]:
```
models.loc['train_ras','logistic_regression'] = roc_auc_score(y_true=y_train, y_score=lr.predict(x_train))
models.loc['cv_ras','logistic_regression'] = roc_auc_score(y_true=y_cv, y_score=lr.predict(x_cv))
models.loc['test_ras','logistic_regression'] = roc_auc_score(y_true=y_test, y_score=lr.predict(x_test))
models.loc['accuracy_score','logistic_regression'] = accuracy_score(y_pred=lr.predict(x_test).round(), y_true=y_test)

models.loc['train_ras','decision_tree'] = roc_auc_score(y_score=d_tree.predict(x_train), y_true=y_train)
models.loc['cv_ras','decision_tree'] = roc_auc_score(y_score=d_tree.predict(x_cv), y_true=y_cv)
models.loc['test_ras','decision_tree'] = roc_auc_score(y_score=d_tree.predict(x_test), y_true=y_test)
models.loc['accuracy_score','decision_tree'] = accuracy_score(y_pred=d_tree.predict(x_test).round(), y_true=y_test)
```

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```
models.loc['train_ras','random_forest'] = roc_auc_score(y_score=rfc.predict(x_train), y_true=y_train)
models.loc['cv_ras','random_forest'] = roc_auc_score(y_score=rfc.predict(x_cv), y_true=y_cv)
models.loc['test_ras','random_forest'] = roc_auc_score(y_score=rfc.predict(x_test), y_true=y_test)
models.loc['accuracy_score','random_forest'] = accuracy_score(y_pred=rfc.predict(x_test).round(), y_true=y_test)

models.loc['train_ras','xgboost'] = roc_auc_score(y_score=Boosting.predict(x_train), y_true=y_train)
models.loc['cv_ras','xgboost'] = roc_auc_score(y_score=Boosting.predict(x_cv), y_true=y_cv)
models.loc['test_ras','xgboost'] = roc_auc_score(y_score=Boosting.predict(x_test), y_true=y_test)
models.loc['accuracy_score','xgboost'] = accuracy_score(y_pred=Boosting.predict(x_test).round(), y_true=y_test)
```

[37]:
```
models
```

[37]:

	logistic_regression	decision_tree	random_forest	xgboost
train_ras	0.725992	0.898886	0.979395	0.999963
cv_ras	0.723882	0.751782	0.97683	0.777027
test_ras	0.727827	0.748978	0.97611	0.775599
_score	0.816987	0.823693	0.987051	0.84833

Copy ...

[38]:
```
#It is clear by analyzing the roc_auc_score and accuracy_score that random forest is the best model
#to do the prediction using the census bureau database. So we will use random forest to proceed
#further for checking model performance on this dataset.
```

[39]:
```
confusion_matrix(y_pred=rfc.predict(x_test), y_true=y_test)
```

[39]:
```
array([[11276,    23],
       [  172,  3588]], dtype=int64)
```

[40]:
```
arr=confusion_matrix(y_pred=rfc.predict(x_test), y_true=y_test)

df_cm = pd.DataFrame(arr, range(2), range(2))
#plt.figure(figsize = (4,3))
sns.set(font_scale=0.8)#for label size
sns.heatmap(df_cm,
            annot=True,
            annot_kws={"size": 25},
            fmt='.5g',
```

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```
[  172,  3588]], dtype=int64)
```

[40]:
```
arr=confusion_matrix(y_pred=rfc.predict(x_test), y_true=y_test)

df_cm = pd.DataFrame(arr, range(2), range(2))
#plt.figure(figsize = (4,3))
sns.set(font_scale=0.8)#for label size
sns.heatmap(df_cm,
            annot=True,
            annot_kws={"size": 25},
            fmt='.5g',
            xticklabels=['Pred : False(sal <=50k)','Pred : True(sal >50k)'],
            yticklabels=['Actual : False(sal <=50k)','Actual : True(sal >50k)'],)# font size
```

[40]: <matplotlib.axes._subplots.AxesSubplot at 0x146e8d7e208>

[41]:
```
#Sometimes it is not sufficient to conclude a model performance only using the accuracy
#score as that can be good due to class imbalance also. So we need to analyse Recall,Precision,
#F1-score which will give a clear statistics on all the available classes in the dataset.
```

[42]:
```
#Manual calculation of Recall, Precision and other statistics
(TN, FP), (FN, TP) = confusion_matrix(y_pred=rfc.predict(x_test), y_true=y_test)
```

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DSM_Machine_Learning_Prc

Code

```
[42]: #Manual calculation of Recall, Precision and other statistics
(TN, FP), (FN, TP) = confusion_matrix(y_pred=rfc.predict(x_test), y_true=y_test)

# Overall accuracy
acc = (TP+TN)/(TP+FP+FN+TN)
# Sensitivity/Recall, hit rate, recall, or true positive rate
TPR = TP/(TP+FN)
# Specificity or true negative rate
TNR = TN/(TN+FP)
# Precision or positive predictive value
PPV = TP/(TP+FP)
# Negative predictive value
NPV = TN/(TN+FN)
# Fall out or false positive rate
FPR = FP/(FP+TN)
# False negative rate
FNR = FN/(TP+FN)
# False discovery rate
FDR = FP/(TP+FP)

print(f"Sensitivity/Recall : {TPR} \nSpecificity:{TNR} \nPrecision : {PPV} \nF1-score : {(2*PPV*TPR)/(PPV+TPR)}")
```

```
Sensitivity/Recall : 0.9542553191489361
Specificity:0.9979644216302328
Precision : 0.9936305732484076
F1-score : 0.9735449735449735
```

```
[43]: # Above statistics manipulation can also be done using the functions implemented in sklearn.metrics as below
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, classification_report
precision_score(y_true=y_test, y_pred=rfc.predict(x_test))
recall_score(y_true=y_test, y_pred=rfc.predict(x_test))
f1_score(y_true=y_test, y_pred=rfc.predict(x_test))
```

```
[43]: 0.9735449735449735
```

```
[44]: #Using classification_report we can get detailed info about each class
print(classification_report(y_true=y_test, y_pred=rfc.predict(x_test)))
```

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DSM_Machine_Learning_Prc

Code

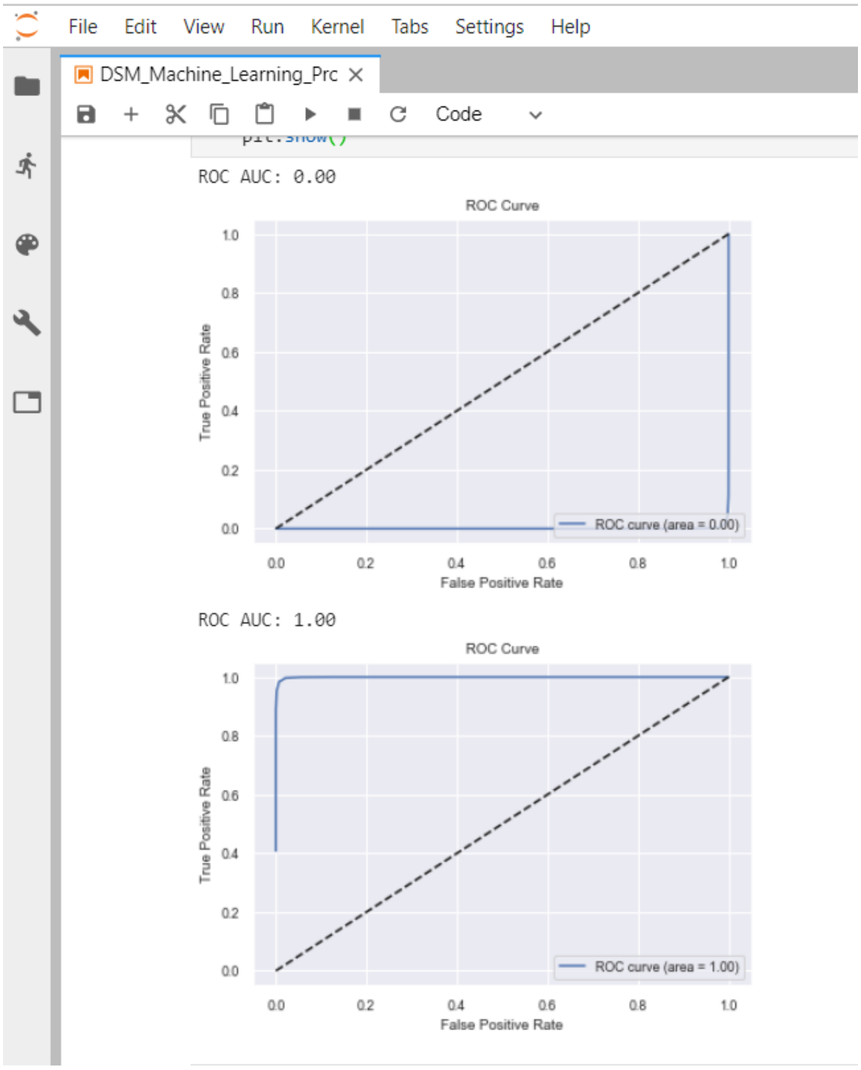
```
[43]: 0.9735449735449735
```

```
[44]: #Using classification_report we can get detailed info about each class
print(classification_report(y_true=y_test, y_pred=rfc.predict(x_test)))
```


```
             precision    recall  f1-score   support

          0       0.98      1.00      0.99     11299
          1       0.99      0.95      0.97      3760

avg / total       0.99      0.99      0.99     15059
```

```
[45]: #Plot ROC Curve and caluclate AUC

for i in range(2): # as there are two classes in our dataset for prediciton

    # Determine the false negative and true negative rates (when i = 0)
    # Determine the false positive and true positive rates (when i = 1)
    fpr, tpr, _ = roc_curve(y_test, rfc.predict_proba(x_test)[:,i])

    # Calculate the AUC (area under curve)
    roc_auc = auc(fpr, tpr)
    print('ROC AUC: %0.2f' % roc_auc)

    # Plot of a ROC curve for a specific class
    plt.figure()
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.plot(fpr, tpr, label='ROC curve (area = %0.2f)' % roc_auc)
    plt.plot([0, 1], [0, 1], 'k--')
    #plt.xlim([0.0, 1.0])
    #plt.ylim([0.0, 1.05])
    plt.title('ROC Curve')
    plt.legend(loc="lower right")
    plt.show()
```

```
ROC AUC: 0.00
```




```
[46]: #Conclusion from ROC Curve : IN curve-1 (used for class 0 : salary <=50k) : AUC - 0 and prediction for this class is happening perfectly.
      #IN curve-1 (used for class 1 : salary >50k) : AUC - 1 and prediction for this class is happening perfectly.
      #So random forest is the best model which is providing best accuracy, precision, recall, F1-score.
```